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HandsOn DB: Managing Data Dependencies involving Human Actions

Mohamed Y. Eltabakh
Worcester Polytechnic Institute, meltabakh@wpi.edu

Walid Aref
Purdue University, aref@cs.wpi.edu

Ahmed Elmagarmid
Qatar Computing Research Institute, aelmagarmid@qf.org.qa

Mourad Ouzzani
Qatar Computing Research Institute, mouzzani@qf.org.qa

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by

Mohamed Eltabakh, Walid Aref, Ahmed Elmagarmid,
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HandsOn DB: Managing Data Dependencies involving Human Actions

Mohamed Eltabakh[1], Walid Aref[2], Ahmed Elmagarmid[3], Mourad Ouzzani[3]
[1] Worcester Polytechnic Institute, MA, USA, meltabakh@cs.wpi.edu
[2] Purdue University, IN, USA, aref@cs.wpi.edu
[3] Qatar Computing Research Institute, Qatar, {aelmagarmid, mouzzani}@qf.org.qa

ABSTRACT

Consider two values, x and y, in the database, where $y = F(x)$. To maintain the consistency of the data, whenever x changes, F needs to be executed to re-compute y and update its value in the database. This is straightforward in the case where F can be executed by the DBMS, e.g., SQL or C function. In this paper, we address the more challenging case where F is a human action, e.g., conducting a wet-lab experiment, taking manual measurements, or collecting instrument readings. In this case, when x changes, y remains invalid (inconsistent with the current value of x) until the human action involved in the derivation is performed and its output result is reflected into the database. Many application domains, e.g., scientific applications in biology, chemistry, and physics, contain multiple such derivations and dependencies that involve human actions. In this paper, we propose *HandsOn DB*, a prototype database engine for managing dependencies that involve human actions while maintaining the consistency of the derived data. *HandsOn DB* includes the following features: (1) semantics and syntax for interfaces through which users can register human activities into the database and express the dependencies among the data items on these activities, (2) mechanisms for invalidating and revalidating the derived data, and (3) new operator semantics that alert users when the returned query results contain potentially invalid data, and enable evaluating queries on either valid data only, or both valid and potentially invalid data. Performance results are presented that study the overheads associated with these features and demonstrate the feasibility and practicality in realizing *HandsOn DB*.

1. INTRODUCTION

In many application domains such as scientific experimentation in biology, chemistry, and physics, the derivations among the data items are complex and may involve sequences of human actions, e.g., conducting a wet-lab experiment, taking manual measurements, and collecting instrument readings. In traditional derived data that are stored inside the database, e.g., deriving age from the date-of-birth attribute, simple procedures internal to the database system can be coded and executed automatically to maintain the consistency of the data. In contrast, when the derivations among the data items involve human actions, these derivations cannot be coded within the database. Hence, updating a database value may render all dependent and derived values invalid until the required human actions are performed and their output results are updated back in the database.

Typical databases may contain multiple dependencies which may cascade and interleave with other dependencies that involve executable functions, e.g., SQL and C functions. Hence, a complex dependency graph is created among the database items. Since human actions may take long time to prepare for and perform, parts of the underlying database may remain inconsistent for long periods of time while the data still need to be made available for querying. Our focus in this paper is on managing dependencies that involve human actions or more generally, real-world activities, inside the database engine while maintaining the consistency of the derived data under update and query operations.

Motivating Examples: Figure 1 illustrates an example, from the biology domain, of a pipeline collecting different pieces of information about genes/proteins and storing them in the database. As depicted in the figure, the initial sequence files stored in the database will be used as input to a set of procedures involving human actions in order to discover more information, e.g., the protein family, gene function, and the location of SNP (Single-Nucleotide Polymorphism). If the underlying sequence data is modified due to correction of sequencing errors or an improved assembly, then the corresponding output data from the procedures become potentially invalid and need to be re-verified. Another example of chemical reactions is illustrated in Figure 2 where chemists may store in the database descriptions of chemical reactions, e.g., substrates, reaction parameters, instruments settings, and products. Clearly, these chemical reactions require human intervention. If, for example, any of the substrates in the reaction are modified, then the products of the reaction may change as well, and hence they become invalid until the reaction is re-executed or the chemist verifies the old value.

The presence of potentially-invalid values in the database directly affects the correctness of the queries' answers as well as any decisions based on the results. For example, continuing with the biology pipeline (Figure 1) assume the

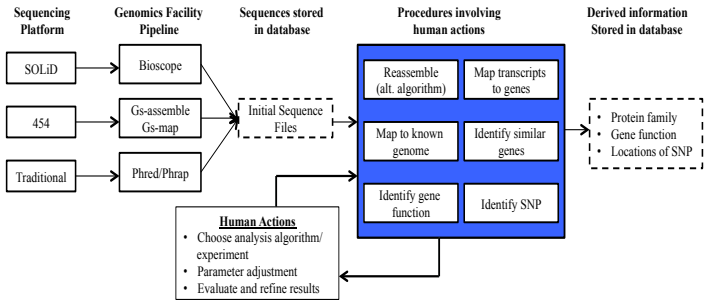


Figure 1: Real-world dependencies in biological pipeline.

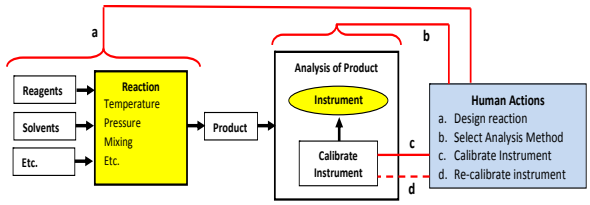


Figure 2: Real-world dependencies in chemical reactions.

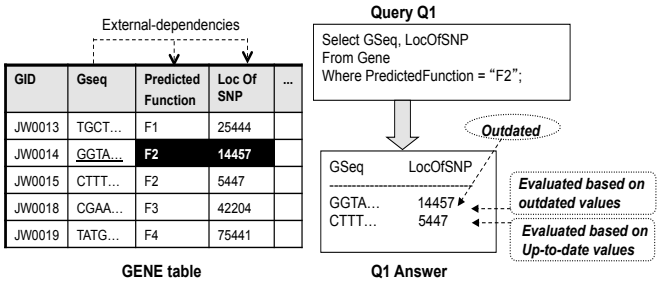


Figure 3: Querying invalid values.

database instance shown in Figure 3 where the sequence of gene *JW0014* has been updated, and hence the dependent values become invalid (marked as black table cells). Although the reported result from query *Q1* seems correct, it is missing crucial information, e.g., the reported value "14457" is potentially invalid and needs to be verified, and the first tuple in the answer matched the query predicate (*PredictedFunction = "F2"*) based on an invalid value *F2*, and hence its presence in the output is questionable.

Candidate Solutions with Current Technology: One possible approach is to store metadata information along with the data values, e.g., a version number or timestamp, to track whether values are up-to-date or outdated. However, this approach has several limitations including: (1) Without explicitly modeling the dependencies inside the DBMS, the maintenance of the auxiliary metadata is delegated to end-users which is both an overwhelming task and error prone. (2) Integrating the metadata information inside the query engine is problematic because users' queries have to incorporate the metadata information in their evaluation. For example, dependencies may span multiple tables, e.g., values in table R depend on values in tables S_i and S_j, and hence a query on only table R needs to be extended to also check tables S_i and S_j to decide whether R's values are up-to-date or outdated, which will make even simple queries very complex. (3) All curation operations, e.g., why certain values are invalid and how to re-validate them, and which external activities need to be performed and using which parameters, will be manually performed without any system support. Another possible approach is to delay the updates to the database until all derived values are computed, i.e., keeping the partial results outside the database. Although feasible in some scenarios involving simple dependencies, it has several limitations as it does not scale with complex dependencies, and storing the data outside the database is not a preferred solution w.r.t. recovery, instant availability of results, and ensuring the consistency of the new values with other database values.

Contribution: The above limitations motivate the need for a more systemic mechanism and an end-to-end solution that enables scientists to focus on running their experiments and uploading the results, instead of tracking the dependencies among the data items and verifying their consistency. In this paper, we propose *HandsOn DB*, a prototype database engine for managing dependencies that involve real-world activities while maintaining the consistency of the derived data. *HandsOn DB* addresses all of the above limitations as it enables users to reflect the updates immediately into the database, i.e., instant availability of the data, while the DBMS keeps track of the derived data by marking them as *potentially invalid* (aka *outdated*) and reflecting their status in the query results, i.e., the consistency of the data is not compromised. *HandsOn DB* introduces extended query operators for evaluating users' queries on either valid data only, thus avoiding relying on any potentially invalid values (no false-positive tuples), or both valid and potentially invalid data (include false-positive tuples). *HandsOn DB* is a component in *bdbms* [**?**, **?**], our proposed database system for scientific data management. We first highlighted the main research challenges involved in managing complex real-world dependencies in [**?**]. In this paper, we propose novel solutions to these challenges.

The contributions of this paper are as follows:

- Proposing new SQL syntax and its corresponding semantics to register real-world activities into the database and to express the dependencies among data items using these activities.
- Introducing an extended relational algebra and new semantics for query operators to alert users of any potentially-invalid data in the query results, and to enable querying either valid data only or both valid and potentially-invalid data.
- Proposing new data manipulation and curation operations for invalidating and revalidating the data, and for keeping track of the real-world activities that need to be performed in order to revalidate the data.
- Experimentally evaluation the proposed features of *HandsOn DB* and demonstrating the system's practicality.

- Proving the correctness of *HandsOn DB* under a given set of user-defined dependencies. That is, the execution of the proposed algorithms is guaranteed both to terminate and to generate a unique final state of the database. *HandsOn DB* is realized via extensions to PostgreSQL and the empirical results show its applicability and practicality.

The rest of the paper is organized as follows. Section 2 overviews the related work. Section 3 presents the needed definitions. Sections 4 and 5 introduce the data manipulation operations as well as the new query operators, respectively. In Section 6, we present several design issues. The performance analysis is presented in Section 7. Section 8 contains concluding remarks.

2. RELATED WORK

The theory of functional dependencies (FDs) in DBMSs, e.g., [**?**, **?**, **?**], is used to model dependencies among data items, infer keys, and systematically normalize database schemas to prevent several inconsistency problems, e.g., redundancy, and update and delete anomalies. However, FDs cannot solve the inconsistency problem raised in this paper mainly because the dependencies that involve real-world activities cannot be modeled or coded inside the database (E.g.,using triggers or user-defined functions) regardless of how well the schema is designed or normalized. The existence of such external activities that cannot be handled by DBMSs triggered the research in long-running transactions, e.g., [**?**, **?**], where a database transaction may involve external activities, e.g., getting a manager's signature to complete a purchase transaction. Systems for long-running transactions took the approach of loosening the ACID properties, using optimistic concurrency control techniques, and using compensating transactions in the case of failures. The key objective of these systems is to keep track of the derived data that are already modified by the transaction to roll them back if needed (compensating transactions). However, long-running transactions do not keep track of the derived data that are still awaiting to be updated and are currently inconsistent, and hence they delegate this inconsistency issue to the end-user without any system support. More importantly, the currently inconsistent values are subject to querying—possibly for long periods of time— without any special query processing or notification mechanisms.

Active databases [**?**, **?**, **?**] provide mechanisms (through triggers) to respond automatically to events taking place either inside or outside the database. The outside events are ultimately mapped to operations that the DBMS can capture, e.g., insertion, deletion, or calling of a user-defined function. Unlike *active databases*, in *HandsOn DB*, a change inside the database, e.g., updating the gene sequence in Figure 3, may trigger the execution of a real-world activity outside the database to update the derived data. Until this activity is performed, the system needs to keep track of all potentially invalid data items, reflect their status over query results, and provide mechanisms for re-validating these invalid items. Active databases do not address these challenges.

Multi-version systems and databases, e.g., [**?**, **?**, **?**], maintain the old and new values of updated data. However, like snapshot databases (which is the focus of this paper), multi-version databases model only the computable dependencies among the data items. And hence, the provided isolation level and consistency degree are based on the traditional notion of transactions. For example, if value v_j depends on value v_i through an external activity, then a transaction updating v_i to v_i' would create a newer version of the database where both v_i' and v_j are viewed as consistent and up-to-date values. Although this is correct with the traditional notion of transactions, it is semantically incorrect because the external dependency is not taken into account. Extending the proposed techniques in the context multi-version databases is left as future work, and in this case, the history of dependencies changing over time can be also maintained.

Some systems such as checkout\checkin systems [**?**] consider querying an old consistent version of the data while updating an *off-line* version until all required changes to all dependent data items have been performed. Then, the off-line version is released as the newer consistent version. The drawbacks of this approach include violating the need for making users' updates available as early as possible, hiding possible data corrections for unbounded long delays, and resolving any consistency issues outside the DBMS, i.e., data conflicts are resolved at the checkin time using version-control systems outside the DBMS. *HandsOn DB* resolves all these issues within the database system.

Probabilistic and fuzzy database systems (PDBMSs), e.g., [**?**, **?**, **?**, **?**], overlap with *HandsOn DB* assuming that data invalidation introduces uncertainty to the data, e.g., *potentially invalid* values can be viewed as *unknown* values. However, the focus of the two systems is different. In *HandsOn DB* a change in the state of a database value, i.e., being valid or invalid, is triggered by database operations, while in PDBMSs the uncertainty is inherent to the data and is given as external input. These uncertainties do not change over time unless users manually modify them. Therefore, PDBMSs do not address several challenges, that are the core of *HandsOn DB*, such as modeling the dependencies among the data items, keeping track of when and why a data item becomes uncertain (invalid), and keeping track of how to revalidate a data item to become certain (valid).

Provenance management, e.g., [**?**, **?**, **?**, **?**], follows two main approaches; *inversion-based* and *annotation-based*. Inversion-based techniques are not applicable to the problem at hand since we deal with external activities that cannot be executed by the DBMS in the first place. Annotation-based techniques [**?**, **?**, **?**, **?**] lack the ability of modeling and integrating real-world activities inside the database system, and hence the dependency graph involving these external activities cannot be constructed. Annotations, therefore, can neither maintain the consistency of the derived data items (computable or non-computable) nor keep track of pending activities that need to be performed to re-validate the data. Provenance has been also studied extensively in the context of scientific workflows, e.g., [**?**, **?**, **?**, **?**] where workflow systems are instrumented to capture and store the provenance information. In these systems, a database can be a single component within a bigger workflow. Although these systems can capture that certain values in the database are generated from external activities, they have not been designed to track or ensure the consistency of these values once they are in the database. In these systems, the database is treated as a black box within the workflow and all of its operations are hidden from the workflow system. Hence, *HandsOn DB* can be used in conjunction with workflow sys-

tems to achieve stronger consistency of the data.

Other related systems are update exchange systems, e.g., [**?**, **?**], that allow reliable exchange of data among different participants (sites) while tracking their provenance [**?**, **?**]. These systems are complementary to *HandsOn DB* as they focus on providing import/export techniques, publishing mechanisms, and provenance tracking to ensure consistent sharing of data across the different sites. In contrast, *HandsOn DB* focuses on providing mechanisms for maintaining the consistency of the data within each site independently while the data evolve through derivations and updates.

3. MODELING ACTIVITIES & DEPENDENCIES

In this section, we present the formal definitions of activities and dependencies, and show how to model them inside the database. We assume a relational database model, and we use the term *"database cell"* to refer to an attribute value in a single tuple. The value itself can be primitive, e.g., integer or string, or complex, e.g., arrays or bit maps.

Definition **(Real-world Activity):** *A real-world activity (RWA, for short) is an activity that requires human intervention, and hence cannot be executed by the DBMS. RWA takes one or more input parameters and produces one or more output parameters.*

Since real-world activities are very close in definition to functions, we define the concept of a *real-world activity function* that maps a real-world activity to a nondeterministic function inside the database. RWA functions are nondeterministic since RWAs such as lab experiments may not generate the same exact output given the same input parameters.

Definition **(Real-world Activity Function):** *A real-world activity function RWA-F is a nondeterministic function inside the database that represents a real-world activity. RWA-F is of type 'real-world activity' and has a signature that specifies the function name and the input and output types. RWA-F has no associated code.*

Similar to defining SQL, C, or Java functions inside the database, we extend the SQL *Create Function* command to define real-world activity functions as follows:

```
Create Function <activity_name> (<input_types>)
  Returns (<output_types>) As real-world activity;
```

Once real-world activity functions are defined in the database, users can create dependencies among the data items using these functions. Users can also create dependencies among the data items using executable functions, e.g., SQL or C functions. Each dependency defines the function name involved in the dependency, the input parameters to the function (the order of the inputs matters only if the function is executable), and the output parameters from the function.

Definition **(Dependency Instance):** *A dependency instance DI is a dependency between a set of input parameters (database cells) and a set of output parameters (database cells) through a specific execution of a function. A dependency instance is defined as DI= (F, SP, DP), where:*

- ***F:*** The function name involved in the dependency.
- ***SP (Source Parameters):*** A set of database cells that are the input parameters to F.

```
Create Table <R>
(
  <columns_definitions >
  ....
 Add Dependency [<dependency_id>]
 Using <func_name>
 Source <T1.c1[, T2.c2, ...] >
 Destination <R.c'1[, R.c'2, ...]>
 [Where <predicates>]
);
```

```
Alter Table <R>
Add Dependency [<dependency_id>]
Using <func_name>
Source <T1.c1[, T2.c2, ...] >
Destination <R.c'1[, R.c'2, ...]>
[Where <predicates>]
[Invalidate Destination] ;

Alter Table <R>
Drop Dependency <dependency_id>
[Invalidate Destination] ;
```

Figure 4: Adding and dropping dependencies.

- ***DP (Destination Parameters):*** A set of database cells that are the output parameters from F.

If F is of type *real-world activity*, then DI is called *real-world dependency*, otherwise, DI is called *computable dependency*. The dependency of DP on SP is complete in the sense that each database cell in DP depends on all database cells in SP.

Dependency instances are conceptually defined at the cell level, i.e., they capture the dependencies between the database table cells. Such fine-granular level of expressing the dependencies may sometimes involve high overhead as reported in [**?**]. In *HandsOn DB*, we introduce a higher level of abstraction using the *Add Dependency* construct, by which users may define dependencies over one cell, multiple cells, or even entire columns at once. Dependencies are created in (or dropped from) the database using the *Add Dependency* (or *Drop Dependency*) constructs that are augmented to the SQL *Create Table* and *Alter Table* commands as illustrated in Figure 4.

A new dependency is defined over Table R that contains the destination attributes $R.c'_1$, $R.c'_2$, ... of the dependency. The *dependency_id* is a unique id that is either defined by the user or generated automatically by the system. If the dependency applies to multiple destination tables, then it is defined over each of these tables with different *dependency_id*. The optional *Where* clause contains join and selection predicates over the source and destination tables to specify the exact table cells that are linked together. Examples 1 and 2 below illustrate defining dependencies over single and multiple tables.

Example 1: Single-table dependency

```
Create Table Gene(
  GID text  primary key,
  GSeq text,
  GDirction char,
  GFunction text,
  ...
  ADD Dependency
  Using GeneFunExp
  Source GSeq, GDirection
  Destination GFucntion);
```

Description: Each gene function is inferred from the corresponding gene's sequence and direction the using *GeneFunExp*.

Example 2: Cross-table dependency

```
Create Table Protein(
  PID text primary key,
  GID text references Gene(GID),
  PSeq text,
  PFunction text,
  ...
  ADD Dependency Using A-Prediction
  Source Gene.GSeq, Gene.GDirection
  Destination Protein.PSeq
  Where Protein.GID = Gene.GID
  And Gene.GFunction = 'F1',
  ADD Dependency Using B-Prediction
  Source Gene.GSeq
  Destination Protein.PSeq
  Where Protein.GID = Gene.GID
  And Gene.GFunction != 'F1');
```

Description: For proteins whose gene functions = 'F1', the protein sequence is inferred from the corresponding gene's sequence and direction using *A-Prediction*. Otherwise, the protein sequence is inferred from only the gene's sequence using *B-Prediction*.

In Example 1, the *Where* clause is omitted which indicates that the source and destination table cells belong to the same tuple. In this example, The dependency definition applies

	c.Status = 0 (up-to-date)	c.Status = 1 (outdated)
Invalidate(c)	- c.Status = 1 - For each c' in **RealworldOutputs**(c) -invalidate(c') - For each c' in **ComputableOutputs**(c) -invalidate(c')	-------
Validate(c)	-------	-If each c' in **InputParameters**(c) is valid -c.status = 0 - For each c' in **ComputableOutputs**(c) -validate(c')
Update(c)	- For each c' in **RealworldOutputs**(c) -Invalidate(c') - For each c' in **ComputableOutputs**(c) -update(c')	-If each c' in **InputParameters**(c) is valid - c.status = 0 - For each c' in **ComputableOutputs**(c) -update(c')

Insert(t)	Delete(t): Reject if dependents exist	Delete(t): Propagate Invalidation
-Insert t -For each database cell c in t -If c' in **InputParameters**(c) is invalid Then -invalidate(c')	-For each database cell c in t -If **ComputableOutputs**(c) not empty Or **RealworldOutputs**(c) not empty -Reject deletion and rollback -Delete t	-For each table cell c in t -invalidate(c) -Delete t

Figure 5: Procedures for data manipulation operations.

to all tuples in table `GENE`. In Example 2, the dependencies are defined between the two tables, `GENE` and `PROTEIN`. In this case, the *Where* clause contains a join between the two tables. Join predicates are mandatory for cross-table dependencies and are restricted to only equality joins between a foreign key in the destination table, e.g., *Protein.GID*, and the primary key in the source table, e.g., *Gene.GID*. This restriction ensures that each destination table cell is attached to unique source table cells. Notice that the predicates of the two *Add Dependency* constructs in Example 2 are not disjoint, i.e., one tuple may have the gene function equals *"F1"* and the start position greater than 10000. In this case, the destination table cell of that tuple, i.e., the protein sequence, follows the definition of the second dependency (the most recent one) as will be explained using the *overriding* property in Section 4.

4. DATA MANIPULATION OPERATIONS

In this section, we present the data manipulation operations in *HandesOn DB* and define how they affect the value and status of the database cells. These operations represent the interfaces through which the dependency graph—created from the user-defined real-world and computable dependencies—is manipulated. Conceptually, each table cell has a status (0 = up-to-date, 1 = outdated) in addition to the cell value. That is, Relation R having n attributes is represented as:

$R = \{r =< (C_1.value, C_1.status), ..., (C_n.value, C_n.status) >\}$.

We define five data manipulation operations, namely, *insert(t)*, *delete(t)*, *update(c)*, *invalidate(c)*, and *validate(c)*, where t is a tuple and c is a database cell. In Figure 6, we demonstrate a sequence of cumulative operations over two sample tables T and S. Tuples in S reference the tuples in T using the foreign and primary keys $S.T\_fk$, and $T.T\_pk$, respectively. The dependencies among the two tables are depicted in Figure 6(a), where the dashed and solid lines represent computable and real-world dependencies, respectively. The semantics of each dependency are presented in Figure 6(b). Figure 6(c) gives the state of the database after performing each operation. The black-marked table cells represent the outdated values while the red-marked ones represent modified or newly inserted values.

Throughout this section, we use the following shorthand notations for a given database cell c. The database cells from which c is derived are called *InputParameters(c)*. The database cells that are derived from c through real-world and computable dependencies are called *RealworldOutputs(c)*, and *ComputableOutputs(c)*, respectively. The procedures for the data manipulation operations are summarized in Figure 5.

• **invalidate(c):** invalidates c and all database cells that depend on c recursively, i.e., database cells in *ComputableOutputs(c)* and *RealworldOutputs(c)*. For example, when Operation 1 in Figure 6 invalidates the database cell (t4,r1) because of the existence of the real-world activity *F2*, the invalidation propagates recursively to the dependent database cells (t5,r1), (s1,r1), and (s3, r1).

• **validate(c):** validates c only if *InputParameters(c)*, are all up-to-date. If c is validated, then the *validate* procedure is called recursively on the database cells in *ComputableOutputs(c)* (See Figure 5). The database cells in *RealworldOutputs(c)* are not validated automatically because they are waiting on real-world activities to be performed. Referring to Operation 2 in Figure 6, when Activity *F2* is externally performed and its result (value 13) is updated in (t4, r1), the dependent table cell (t5, r1) is re-computed and validated automatically through the computable dependency involving *F3*. However, the validation does not propagate to (s1, r1) because *F4* is a real-world activity.

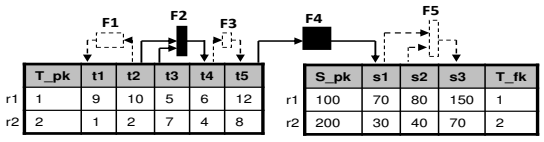
• **update(c):** updates the value of c as well as the values of *ComputableOutputs(c)*. If c is currently invalid, then c is validated only if *InputParameters(c)* are all valid. Otherwise, the status of c remains unchanged. Moreover, since the value of c is modified, the database cells in *RealworldOutputs(c)* are invalidated (See Figure 5). For example, Operation 1 in Figure 6 re-computes and modifies the value of (t1, r1) from '9' to '3' while maintaining its status valid. In contrast, the value in (t4, r1) is invalidated through the real-world dependency involving *F2*. Similarly, Operation 3 results in re-computing the value in (s3,r1) to be '90' instead of '150' through *F5*. However, this update does not validate (s3,r1) because one of its input parameters, i.e., (s1,r1), is still outdated.

• **delete(t):** If the values in t are neither source nor destination parameters to any dependency, then t is deleted without any further processing. The same rule applies if the values in t are only destination parameters to some existing dependencies. However, if the values in t are source parameters to some existing dependencies, then either the deletion of t is rejected, or t is deleted and the destination parameters of these dependencies are invalidated. The default behavior in the system is to reject the deletion of t. This behavior can be altered at the table level using the following command:

```
9    Alter Table <tableName> Add Constraint <const-
Name>
   On Delete Propagate Invalidation;
```

Both deletion procedures are presented in Figure 5.

• **insert(t):** One of the restrictions on the *Add Dependency* construct is that the destination table has to contain foreign keys that reference the primary keys in the source tables (Refer to Section 3). This restriction ensures the uniqueness of the source table cells for a given destination table cell. It also simplifies the insertion procedure since it



	T_pk	t1	t2	t3	t4	t5
r1	1	9	10	5	6	12
r2	2	1	2	7	4	8

T

	S_pk	s1	s2	s3	T_fk
r1	100	70	80	150	1
r2	200	30	40	70	2

S

(a) User-defined dependencies over sample tables T and S

Dependency function	Type	Description	Source(s)	Dest.	Predicate(s)
F1	Computable	Subtract one from the source	T.t2	T.t1	None
F2	Real-world	Wet-lab experiment	T.t2, T.t3	T.t4	None
F3	Computable	Multiply the source by 2	T.t4	T.t5	None
F4	Real-world	Wet-lab experiment	T.t5	S.s1	S.T_fk = T.T_pk
F5	computable	Sum the sources	S.s1, S.s2	S.s3	None
F6 (in Op# 7)	Real-world	Wet-lab experiment	S.s1	S.s3	None

(b) Dependencies details

Op.#	Operation	Triggering event	Consequence	Database state after the operation
1	Update cell (t2,r1) from 10 to 4	---	-Update cell (t1,r1) with value 3 -Invalidate cell (t4,r1) -Invalidate cell (t5, r1) -Invalidate cell (s1,r1) -Invalidate cell (s3,r1)	T: r1: 1, 3, 4, 5, 6, 12; r2: 2, 1, 2, 7, 4, 8 S: r1: 100, 70, 80, 150, 1; r2: 200, 30, 40, 70, 2
2	Update cell (t4,r1) from 6 to 13	Activity *F2* is conducted using the current values of cells (t2,r1) and (t3,r1). The output value is 13	-Validate cell (t4, r1) -Update cell (t5,r1) with value 26 -Validate cell (t5,r1)	T: r1: 1, 3, 4, 5, 13, 26; r2: 2, 1, 2, 7, 4, 8 S: r1: 100, 70, 80, 150, 1; r2: 200, 30, 40, 70, 2
3	Update cell (s2,r1) from 80 to 20	---	-Update cell (s3,r1) with value 90	T: r1: 1, 3, 4, 5, 13, 26; r2: 2, 1, 2, 7, 4, 8 S: r1: 100, 70, 20, 90, 1; r2: 200, 30, 40, 70, 2
4	Insert into T tuple r3	---	---	T: r1: 1, 3, 4, 5, 13, 26; r2: 2, 1, 2, 7, 4, 8; r3: 3, 8, 9, 4, 7, 14 S: r1: 100, 70, 20, 90, 1; r2: 200, 30, 40, 70, 2
5	Update cell (t3,r3) from 4 to 8	---	-Invalidate cell (t4,r3) -Invalidate cell (t5, r3)	T: r1: 1, 3, 4, 5, 13, 26; r2: 2, 1, 2, 7, 4, 8; r3: 3, 8, 9, 8, 7, 14 S: r1: 100, 70, 20, 90, 1; r2: 200, 30, 40, 70, 2
6	Insert into S tuple r3	---	-Invalidate cell (s1,r3) -Invalidate cell (s3,r3)	T: r1: 1, 3, 4, 5, 13, 26; r2: 2, 1, 2, 7, 4, 8; r3: 3, 8, 9, 8, 7, 14 S: r1: 100, 70, 20, 90, 1; r2: 200, 30, 40, 70, 2; r3: 300, 3, 13, 16, 3
7	Alter Table S Add Dependency Using F6 Source S.s1 Destination S.s3 Invalidate destination;	The derivation mechanism of Column S.s3 is modified.	-For each database cell c in S.s3 -Invalidate (c) -For each database cell c in S.s3 -The new dependency overrides the old one	T: r1: 1, 3, 4, 5, 13, 26; r2: 2, 1, 2, 7, 4, 8; r3: 3, 8, 9, 8, 7, 14 S: r1: 100, 70, 20, 90, 1; r2: 200, 30, 40, 70, 2; r3: 300, 3, 13, 16, 3

(c) Sequence of database operations and their effect on the database (dark cells represent invalid values)

Figure 6: Examples of database operations under a set of user-defined dependencies.

ensures that at the insertion time of t, there cannot be destination parameters in the database that depend on t. The default action is to insert t into the database with all its values up-to-date and no further processing is needed. The only exception is when the values of t are destination parameters to some existing real-world or computable dependencies. In this case, for each database cell c in t, if any of the *InputParameters(c)* is invalid, then c is invalidated (See Figure 5). For example, Operation 4 in Figure 6 inserts a new tuple *T.r3* with all its values up-to-date. In contrast, Operation 6 inserts tuple *S.r3* (which references tuple *T.r3*) and invalidates the value in (s1,r3) because this value is inferred from (t5,r3), which is currently invalid.

Other operations that may affect the status of the database items are adding and dropping dependencies. When a new dependency, say DI, is added to the database, we need to address two issues: (1) whether or not DI will form a cycle with other existing dependencies, and (2) whether or not DI will override other existing dependencies.

A cycle among a set of user-defined dependencies indicates that the derivations among the destination and source parameters of these dependencies may loop indefinitely. Cycles are not allowed in *HandsOn DB* according to the following definitions— Recall that $DI.DP$ and $DI.SP$ correspond to the destination and source parameters of dependency DI, respectively.

Definition **(Cycle Formation):** *Dependency instances* DI_1, DI_2, ..., DI_n *form a cycle if* $DI_i.DP \cap DI_{i+1}.SP \neq \phi$, *for* $1 \leq i < n$, *and* $DI_n.DP \cap DI_1.SP \neq \phi$.

Property **(Cycle-Free Dependency Graph):** *A newly defined dependency instance* DI_i *is rejected by the system if* $\exists$ *dependency instances* DI_j, DI_k, ..., DI_n | $DI_i \cup DI_j$, DI_k, ..., DI_n *form a cycle.*

The algorithm for detecting and preventing cycles among the dependencies is discussed in Section 6.1.

Since the derivations among the data items may change over time, the user-defined dependencies may change over time as well, i.e., new dependencies may *override* other existing dependencies. For example, if a database cell c is a destination parameter to dependency DI_j and a new depen-

OID	Attr-1	Attr-2	...	Attr-N
1	a1	b1	...	v1
2	**a2**	b2	...	v2
3	a3	b3	...	**v2**
4	**a4**	b4	...	v4
5	A5	b5	...	**v5**
6	a3	b6	...	v7

(a) Example of Database Instance.
*Black-marked values are potentially-invalid.

Predicate 1	Predicate 2
Attr-N = "v2"	Attr-N = "v2" AND Attr-1= "a3"
F	F
T	-ve
+ve	+ve
F	F
-ve	F
F	F

(b) Predicate Evaluation.

Figure 7: Examples of predicate evaluation.

dency DI_i is defined where c is its destination parameter, then DI_i overrides DI_j w.r.t. c. Now c is being derived according to DI_i instead of DI_j. Dependencies DI_i and DI_j may or may not be of the same type (real-world or computable). The overriding property is defined as follows:

Definition **(Dependency Overriding)** *Dependency instance DI_i is said to override dependency instance DI_j w.r.t destination parameters $DP' \neq \phi$ if $DI_i.DP \cap DI_j.DP = DP'$ and DI_i is defined (chronologically) after DI_j.*

Dependency overriding ensures that any database cell c can be a destination parameter to at most one dependency instance at any given time. Hence, there is exactly one way to derive or infer c (if any).

• **Adding/Dropping dependencies:** A new dependency is added to the database using either the extended *Create Table* or *Alter Table* commands (See Section 3). If an added (or dropped) dependency is defined using the *Alter Table* command including the optional *Invalidate Destination* clause, then the destination table cells that satisfy the dependency predicates are invalidated. Otherwise, the destination table cells remain valid. Newly added dependencies may override existing ones. For example, Operation 7 in Figure 6 defines a new dependency indicating that the values in column $S.s3$ are new derived from the RWA-F *F6* instead of the computable dependency involving *F5*. The overriding mechanism is described in detail in Section 6.1.

5. EXTENDED QUERYING MECHANISM

Initially, all values in *HandsOn DB* have a *valid* status. However, as users perform database updates, parts of the underlying database will become *potentially invalid* (under re-evaluation). Thus, it is crucial for end-users to get alerted when their queries touch or depend on potentially invalid values. In this section, we introduce extended semantics for the query operators to annotate the query results with the status information and to enable evaluating queries on either valid data only (avoid getting false positive tuples), or both valid and potentially invalid data (include false positive tuples).

5.1 Predicate Evaluation

A predicate evaluation over a tuple typically results in a boolean value True or False. With the status of each value in the database being up-to-date or outdated, we extend the predicate evaluation to return one of four possible values (4-valued logic): True (T), False (F), Potentially false positive (+ve), and Potentially false negative (-ve). The value *True*

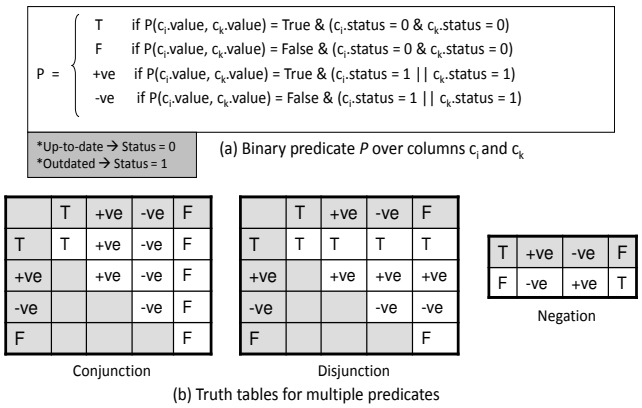


Figure 8: Predicate evaluation rules.

indicates that the tuple qualifies the predicate based on only up-to-date values, and hence, the tuple is certainly part of the answer (e.g., the 2^{nd} tuple against Predicate1 in Figure 7). The value *False* indicates that the tuple disqualifies the predicate based on only up-to-date values, and hence, the tuple is certainly not part of the answer (e.g., the 1^{st} tuple against Predicate1 in Figure 7). The value *Potentially false positive* indicates that the tuple qualifies the predicate but based on outdated values, and hence, the tuple is potentially a false positive (e.g., the 3^{rd} tuple against Predicate1 in Figure 7). The value *Potentially false negative* indicates that the tuple disqualifies the predicate based on outdated values, and hence, the tuple is potentially a false negative (e.g., the 5^{th} tuple against Predicate1 in Figure 7). Although it seems easier to set the potentially-invalid values to Null and use the 3-valued logic supported by most DBMSs, i.e., True, False, and IS NULL, the proposed 4-valued logic has several advantages: (1) Columns in the database may be defined as *Not NULL* and hence the Null value may not be allowed in the first place. (2) Null values are known to be problematic to work with as they mandate the use of special functions, e.g., IS NULL or NVL, when comparing values to avoid nondeterministic evaluation. Nevertheless the complexity of manipulating Null values by query operators such as joins and grouping. (3) Under the 3-valued logic, the query operators still need to be extended to differentiate between the user-inserted Null values and the system-generated Null values, otherwise, simple operation like reporting the potentially-invalid values in a given column cannot be performed.

In Figure 8(a), we present the rules for evaluating binary predicates (*Column <op> Column*)— rules for evaluating unary predicates (*Column <op> constant*) are trivial. As an example, a predicate P over Columns c_i and c_j evaluates to *+ve* if the values of c_i and c_j satisfy P while at least one of the two values is outdated. The truth tables for evaluating multiple predicates are presented in Figure 8(b).

5.2 Query Operators

In this section, we present extended semantics for the query operators. Our goal is that the output produced from the query operators should be both semantically meaningful and easily interpretable by end-users. We extended the selection and join operators with three different semantics to enable retrieving tuples that evaluate the predicate(s) to

either T, +ve, or -ve. The semantics of the other operators, e.g., duplicate elimination and set operators, have been also extended to take both the status and the value of the database items into account while comparing them. The following notations are used in the rest of this section: R and S are relation names, r and s are individual tuples in R and S, respectively, and c_i is a column name. When ambiguous, we use $r.c_i$ to refer to Column c_i in Tuple r.

• ***Selection*:** Tuples that evaluate the selection predicate to T, *+ve*, or *-ve* are of interest since they either satisfy or have the potential to satisfy the query. However, returning these tuples altogether from one operator can be very misleading and hard to interpret. In *HandsOn DB*, we define three types of selection operators, namely, *True Selection* (σ_T), *False-positive Selection* (σ_+), and *False-negative Selection* (σ_-), that return tuples that evaluate to each of T, *+ve*, or *-ve*, respectively. The algebraic expressions of the selection operators are as follows.

***True Selection*($\sigma_{T,P}$):** Selects tuples that evaluate Predicate P to T.

$$\sigma_{T,P}(R) = \{r =< (c_1.value, c_1.status), ..., (c_n.value, c_n.status) > , |P(r) = T\}$$

***False-positive Selection*($\sigma_{+,P}$):** Selects tuples that evaluate Predicate P to *+ve*.

$$\sigma_{+,P}(R) = \{r =< (c_1.value, c_1.status), ..., (c_n.value, c_n.status) > , |P(r) = +ve\}$$

***False-negative Selection*($\sigma_{-,P}$):** Selects tuples that evaluate Predicate P to *-ve*.

$$\sigma_{-,P}(R) = \{r =< (c_1.value, c_1.status), ..., (c_n.value, c_n.status) > , |P(r) = -ve\}$$

• ***Inner Join*:** The evaluation of a join predicate over a pair of tuples r and s results in one of four possible values, i.e., T, *+ve*, *-ve*, or F. Join predicates are binary predicates and hence they follow the evaluation rules presented in Figure 8(a). Similar to the *selection* operator, we define three types of join operators, namely, *True Join*, *False-positive Join*, and *False-negative Join*, that return tuples that evaluate to each of the values T, *+ve*, *-ve*, respectively. The algebraic expression of the *True Join* operator is as follows.

***True Join*($R \bowtie_{T,P} S$):** Returns the joined tuples r and s that evaluate predicate P to T.

$$R \bowtie_{T,P} S = \{z =< (r_1.value, r_1.status), ..., (s_1.value, s_1.status), ..., (s_m.value, s_m.status) > |P(z) = T\}$$

The algebraic expressions of the *False-positive* ($\bowtie_{+,P}$) and *False-negative* ($\bowtie_{-,P}$) join operators are similar to that of the *True* join operator with the exception of having Join Predicate *P(z)* evaluates to *+ve* and *-ve*, respectively.

• ***Duplicate Elimination* & *Set operations*:** Two tuples are considered identical iff they share the same value and status for all their attributes. More formally, tuples r and s are considered identical w.r.t. Columns c_1, c_2, ..., c_n iff: $(r.c_i.value = s.c_i.value \text{ and } r.c_i.status = s.c_i.status) \; \forall \; i \in \{1, 2, ..., n\}$. Duplicate elimination and set operators, i.e., union, intersect, and except, are extended based on this semantics. Note that these operators do not have the notion of *+ve* and *-ve* evaluation. The reason is that two identical and invalid tuples may be invalid for different reasons, however, since no extra information, e.g., the reason of invalidation, is carried out with the tuples in the output, they cannot be distinguished from each other. Hence, reporting all the instances becomes very confusing and carries no additional information to users, instead we chose to implement the standard semantics and report only one instance of such tuples to indicate the existence of such combination. In Section 6.3, we present a set of curation operators that track why certain tuples are invalid and report their dependencies.

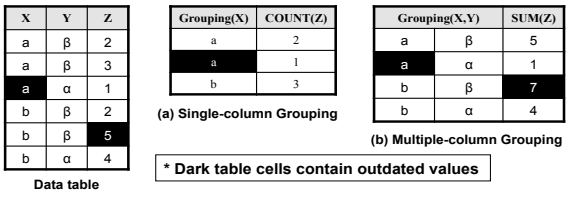


Figure 9: Example of grouping and aggregation.

• ***Grouping*($\gamma(R)$):** Consistent with the semantics of identical tuples, tuples that have the same values and status in the grouping columns are added to the same group. Therefore, two identical values with different status will form two different groups with different status as well. For example, the grouping over column X in Figure 9(a) results in producing two groups for value a; one up-to-date and one outdated.

• ***Aggregation*($\eta(R)$):** An aggregate function, e.g., SUM, AVG, COUNT, aggregates a set of up-to-date and outdated values and returns a single value. The question is: What will the status of the returned value be? We categorize the aggregate functions into two categories, *value-insensitive* and *value-sensitive* aggregators. A value-insensitive aggregator, e.g., COUNT, always returns a value with an up-to-date status. The reason is that the result from a value-insensitive aggregator does not depend on the actual values in the aggregated set. For example, the group corresponding to value b in Figure 9(a) has *count(Z)* equals 3 with up-to-date status although one of the values are outdated. In contrast, a value-sensitive aggregator, e.g., SUM, AVG, MIN, or MAX, returns a value with an up-to-date status only if all the values in the aggregated set are up-to-date, otherwise the returned value will have an outdated status. For example, the group corresponding to the pair (b, β) in Figure 9(b) has *sum(Z)* equals 7 with outdated status since the sum depends on the outdated value 5.

We extend the SQL *select* statement to include the newly proposed operators. A comparison operator may be suffixed with *'@'*, *'+'*, or *'-'* to indicate a *true*, *false-positive* or *false-negative* evaluation, respectively.

Example: Consider the following extended query:

```
9 Select GSeq, PSeq From GENE G, PROTEIN P
   Where G.GID =+ P.GID And GFunction =- 'F2';
```

where $=+$, and $=-$ correspond to *false-positive* and *false-negative* equality operators, respectively. The query is equivalent to the algebraic expression:

$$\pi_{GSeq,PSeq}(\sigma_{-,GFunction='F2'}(GENE \bowtie_{+,G.GID=P.GID} PROTEIN))$$

6. DESIGN ISSUES

As discussed in Section 3, the user-defined dependencies create a dependency graph among the database cells. Since the graph may grow massively, materializing and storing it inside the database may involve unnecessary and substantial overhead. Therefore, *HandsOn DB* utilizes the powerful triggering mechanism in database systems by dynamically generating triggers that enforce the user-defined dependencies and propagate the (in)validation operations accordingly (Section 6.1). The maintenance of the real-world activities pending execution is presented in Section 6.2.

***Storage Scheme*:** For each dependency, we store in catalog tables the dependency definition, the names of the source and destination tables and columns, the type of the dependency as either *computable* or *real-world*, and a unique identifier (dependency_id) that is assigned to the dependency at the creation time (See the *Add Dependency* construct in Section 3). For each table cell c, in addition to c's value, we keep two additional system-maintained fields *c_status* and *c_dependency_id*, where *c_status* indicates whether c is up-to-date ($status = 0$) or outdated ($status = 1$), and *c_dependency_id* stores the id of the most recent dependency to which c is a destination parameter (if dependency_id is *null*, then c does not depend on other values in the database). When a new dependency having dependency_id, say v_i, is added to the database, all destination table cells belonging to this dependency will have their dependency_id field updated to v_i.

6.1 Realization of Dependencies using Triggers

When a new dependency is added to the database, the system extracts the predicates from the *Add Dependency* construct and automatically generates triggers that enforce the dependency. The processing of a given *Add Dependency* construct involves four steps: (1) detecting whether or not the new dependency forms a cycle with the already existing dependencies, (2) assigning a unique id v_i to the dependency, (3) generating a set of triggers over the source and destination tables to enforce the dependency, and (4) overriding other existing dependencies by modifying the *dependency_id* field of the destination parameters of the new dependency to v_i.

Formation of cycles: Testing the formation of a cycle among the user-defined dependencies can be very expensive if performed at the cell level. *HandsOn DB*, therefore, detects cycles in two phases; *filter* (column_level test) and *refine* (cell_level test). The intuition is that if no dependency is found between columns $T.c_i$ and $T.c_j$, then there is no need to check the values in these columns (the filter phase). If a dependency is found between $T.c_i$ and $T.c_j$, then we need to perform the more-expensive step and check which exact table cells have the dependencies (the refine phase). In the filter phase, we maintain a *precedence graph* among the database columns, where an edge is added from column $T.c_i$ to column $S.c_j$ if $T.c_i$ and $S.c_j$ are source and destination columns in a given dependency, respectively. If the new dependency will not form a cycle in the *precedence graph*, then the dependency is added to the database. Otherwise, we move to the more-expensive refine phase in which we check whether the candidate cycle at the column level forms a real cycle at the cell level. In the refine phase, we form a temporary table, say $Temp_i(Src,\ Dest)$, for each dependency, say D_i, involved in the column-level cycle. $Temp_i$ contains the tuple ids of the source and destination table cells for dependency D_i (temporary tables can be expressed as queries without materializing them). The temporary tables are then joined so that $Temp_i.Dest = Temp_{i+1}.Src$, where $1 \leq i \leq n-1$, and $Temp_n.Dest = Temp_1.Src$ (assuming the column-level cycle is of length n). If the query returns any results, then there exists a cell-level cycle, and the new dependency is rejected. Otherwise, the new dependency is added to the database. Notice that if the new dependency passes the refine phase, then any insertions or updates to the base tables involved in the column-level cycle need to be checked to ensure that they will not form a cycle in the future. This check is not expensive since it will be performed only for the newly inserted or updated tuple.

In principle, given a new dependency definition, *HandsOn DB* creates automatically several triggers to enforce the dependency and to propagate the status to dependent values. In Figures 10(a) and (b), we present the *After Update* code templates for *real-world*, and *computable* dependencies, re-

```
1 src_list = the set of all source cells involved in the dependency other than T_i.c_i;
2 dest_cell = the destination cell of the dependency;
3 IF (dest_cell.dependency_id ≠ v_i) THEN
4     Return;
5 END IF;
6 IF ((dest_cell != null) and (c_i.old != c_i.new)) THEN
7     IF (c_i_Status.old = c_i_Status.new = "up-to-date") THEN
8         IF (status of all cells in src_list is "up-to-date") THEN
9             -- Insert a pending record into PendingActivity to request an
                  execution of function F using src_list and T_i.c_i as inputs;
10        END IF
11        -- Update the status of dest_cell to "outdated";
12    ELSE IF (c_i_Status.old = "outdated" and c_i_Status.new = "up-to-date") THEN
13        IF (status of all cells in src_list is "up-to-date") THEN
14            -- Insert a pending record into PendingActivity to a request an
                  execution of function F using src_list and T_i.c_i as inputs;
15        END IF
16    END IF
17 ELSE IF ((dest_cell != null) and (c_i_Status.old != c_i_Status.new)) THEN
18    IF (c_i_Status.old = "up-to-date" and c_i_Status.new = "outdated") THEN
19        IF (dest_cell.status = "outdated") THEN
20            IF (status of all cells in src_list is "up-to-date") THEN
21                -- Insert a compensating record into PendingActivity
22            END IF;
23        ELSE
24            -- Update the status of dest_cell to "outdated";
25        END IF;
26    ELSE IF (c_i_Status.old = "outdated" and c_i_Status.new = "up-to-date") THEN
27        IF (status of all cells in src_list is "up-to-date") THEN
28            -- Insert a pending record into PendingActivity to request an
                  execution of function F using src_list and T_i.c_i as inputs;
29        END IF
30    END IF
31 END IF
```

(a) Template for *real-world activity* function *F* over source column $T_i.c_i$

```
1 src_list = the set of all source cells involved in the dependency other than T_i.c_i;
2 dest_cell = the destination cell of the dependency ;
3 IF (dest_cell.dependency_id ≠ v_i) THEN
4     Return;
5 END IF;
6 IF ((dest_cell != null) and (c_i.old != c_i.new)) THEN
7     Call function F using src_list and T_i.c_i as inputs to update dest_cell.value;
8     IF (status of all cells in src_list is "up-to-date") THEN
9         -- Update the status of dest_cell to "up-to-date";
10    END IF
11 ELSE IF ((dest_cell != null) and (c_i_Status.old != c_i_Status.new)) THEN
12    IF (c_i_Status.old = "up-to-date" and c_i_Status.new = "outdated") THEN
13        -- Update the status of dest_cell to "outdated";
14    ELSE IF (status of all cells in src_list is "up-to-date") THEN
15        -- Update the status of dest_cell to "up-to-date";
16    END IF
17 END IF
```

(b) Template for c*omputable* function *F* over source column $T_i.c_i$

Figure 10: Templates for *Add Dependency* constructs.

spectively. Consider the template in Figure 10(a). The trigger fires when an update occurs to a tuple, say t, in Table T_i. Column c_i is the source column in the dependency. Lines 1 and 2 retrieve the source and destination table cells involved in the dependency. If the *dependency_id* value of the destination table cell does not match with the id value assigned to the dependency when defined (v_i), then the trigger terminates because the destination cell is no longer a destination parameter to this dependency (Lines 3-5). Lines 7-11 handle the case when the value of c_i is updated while its status remains the same. If the status of c_i as well as all other source parameters of the dependency are up-to-date, then a request record is inserted into the *PendingActivity* table (See Section 6.2) to indicate that the involved real-world activity should be performed based on the new value of c_i (Line 9). In Line 11, the destination table cell of the dependency is marked *outdated*. The *PendingActivity* table is maintained and populated automatically to help users identify which *real-world* activities are ready for execution as will be presented in Section 6.2. Lines 12-15 handle the case when the value is updated and the status is modified from *outdated* to *up-to-date*. In this case, a request record is inserted into *PendingActivity* only if all other source cells are up-to-date (Line 14). Notice that *dest_cell* remains outdated until the real-world activity is performed.

The second part of the template (Lines 17-31) handles a change in the status of c_i without changing its value. In the case when the status of c_i is modified from *up-to-date* to *outdated*, *dest_cell* is marked *outdated* if it is currently up-to-date (Line 24). However, if *dest_cell* is currently outdated and all the other source table cells are up-to-date, then a previous request must have been inserted into *PendingActivity* to validate *dest_cell*. This request can no longer validate *dest_cell* because c_i is now invalid. For this reason, we insert a *compensating* record (Line 21) into *PendingActivity* to prevent the previous request from validating *dest_cell* as will be discussed in Section 6.2. In the case when the status of c_i is modified from *outdated* to *up-to-date*, then a request record is inserted into *PendingActivity* only if all other source cells are up-to-date (Line 28).

The *computable-function* template in Figure 10(b) is a simplified version of that in Figure 10(a). An important difference to note is that since the function involved in the dependency is computable, the trigger executes this function automatically to update *dest_cell* whenever the value of c_i is modified (Line 7). Another key difference is that whenever all the source parameters become up-to-date, the destination parameter is automatically marked as up-to-date (Lines 9, 15). This is unlike the case of the real-world dependencies in which a request record is inserted into *PendingActivity*.

6.2 Logging and Resuming Pending Activities

When a real-world activity function F has all its source parameters up-to-date but its destination parameter outdated, a request record (of type *pending*) for F is inserted into the *PendingActivity* table (Lines 9, 14, and 28 in Figure 10(a)). Before serving that request, i.e., executing F and reflecting its output value into the database, the source parameters of F may change again, or may get invalidated. In the former case, more *pending* requests for executing F are inserted into *PendingActivity*. Users have the option to either serve these requests sequentially or serve only the last request (See the *Resume Function* command below). In the latter case, a *compensating* record is inserted into *PendingActivity* (Line 21 in Figure 10(a)) to indicate that any previous pending requests for executing F can still be served to update the value of the destination table cell but without validating it.

```
1  IF (the request status is "completed", "overwritten", or "compensating") THEN
2      Return;
3  END IF;

4  IF (there exist previous pending requests for the same destination table cell) THEN
5      IF (cascade flag is False) THEN
6          Return;
7      ELSE
8          update the status of these previous requests to "overwritten";
9      END IF;
10 END IF;

11 IF (there exist more recent requests for the same destination cell) THEN
12     update the value of the destination table cell without validating it;
13 ELSE
14     update the value of the destination table cell and mark it as "up-to-date";
15 END IF;

16 Update the status of the request to "completed";
```

Figure 11: Processing the *PendingActivity* records.

A request record consists of the following fields: a unique request id, the function name F to be externally executed, the input arguments to F, an update statement that updates the destination table cell once the new results from F are known, and a status field that shows the status of the request. The status field takes one of the following values: *pending*, *completed*, *overwritten*, or *compensating*. When F is performed and its output result is available, the result is passed to the system using the following command:

```
9  Resume Function <func_name> Value <func_output>
     References <RequestId> [Cascade];
```

where *RequestId* references the unique request id that is assigned to each request in *PendingActivity*. The procedure for executing the *Resume Function* command is presented in Figure 11. If the request has a status of either *completed*, *overwritten*, or *compensating*, then the procedure terminates without further processing (Lines 1-3). If there are previous pending requests targeting the same destination table cell and the optional *Cascade* keyword is not specified, then the procedure terminates because, in this case, requests have to be served in order (Line 6). If *Cascade* is included, then any previous pending requests are marked as *overwritten* and the current request is served (Line 8). Lines 12 and 14 update the value of the destination table cell, and depending on whether or not there are requests more recent than the one currently at hand, the destination table cell either remains invalid (Line 12) or gets validated (Line 14).

The intuition behind updating the destination table cell using the *Resume Function* command instead of the SQL *update* command is that in the latter case the DBMS cannot tell which input arguments are taken into account when executing F. Hence, the DBMS cannot decide whether or not the new output value of F is consistent with the source parameters currently exist in the database.

6.3 Curation Operators

HandsOn DB provides a set of curation operators that help users managing and tracing the dependencies among the data. The query and curation operators are complementary to each other where the former operators allow users to seamlessly query the data, the latter operators allow users

to track why certain tuples/values are invalid and how to validate them. In this section, we present three of these curation operators, i.e., dependency tracking (*DTrack*), hierarchical dependency tracking (*HDTrack*), and dependency roots (*DRoots*). All the operators execute over the output from an SQL *select* statement as depicted below.

```
[DTrack | HDTrack | DRoots] (
    Select *
    From <table name>
    Where <predicates> );
```

For each output tuple t from the select statement, the *DTrack* operator reports for each attribute value v in t, the status of v, the dependency id to which v is a destination, and the source table cells on which v depends. *DTrack* starts by retrieving the *c_dependency_id* values stored in t and then based on the dependency definitions, it executes a reverse query to retrieve the source table cells. The *HDTrack* operator executes in a similar way as *DTrack* except that it reports the complete hierarchy of dependencies until it reaches values with no further dependencies, i.e., *HDTrack* recursively executes *DTrack* until no further dependencies can be found. Both *DTrack* and *HDTrack* help users to trace the dependencies upward in order to re-validate certain values. *DRoots*, on the other hand, reports all invalid values within the selected tuples that depend only on all up-to-date values—and hence they are the ones to start re-validating (the roots). To find the roots in a given set of tuples, *DRoots* scans the *Pending Activity* table (Refer to Section 6.2) for records with pending status and no compensating counterparts. The destination table cells in these records are the set of roots in the database which will then be filtered based on the user's selection.

6.4 Correctness of Execution

In this section, we study two important properties of the data manipulation operations defined as follows:

- ***Termination:*** *The procedures of the data manipulation operations are guaranteed to terminate after a set of database modifications.*
- ***Confluence:*** *The final state of the database after any of the data manipulation procedures is unique. That is, the order in which non-prioritized dependencies (dependencies that do not have precedence among each other) are triggered always leads to the same final state of the database.*

These two properties have been studied in the context of active databases [**?**]. In the following, we prove that both properties hold under a given set of user-defined dependencies.

(I) Termination:
It is proven in [**?**] (Theorem 5.1) that if the user-defined rules do not form a cycle, then the execution is guaranteed to terminate. In our model, the user-defined dependencies are not allowed to form cycles as presented in Section 4. Therefore, the following theorem holds.

Theorem 1 (Termination): *The procedures of the data manipulation operations are guaranteed to terminate after a set of database modifications.*

(II) Confluence:

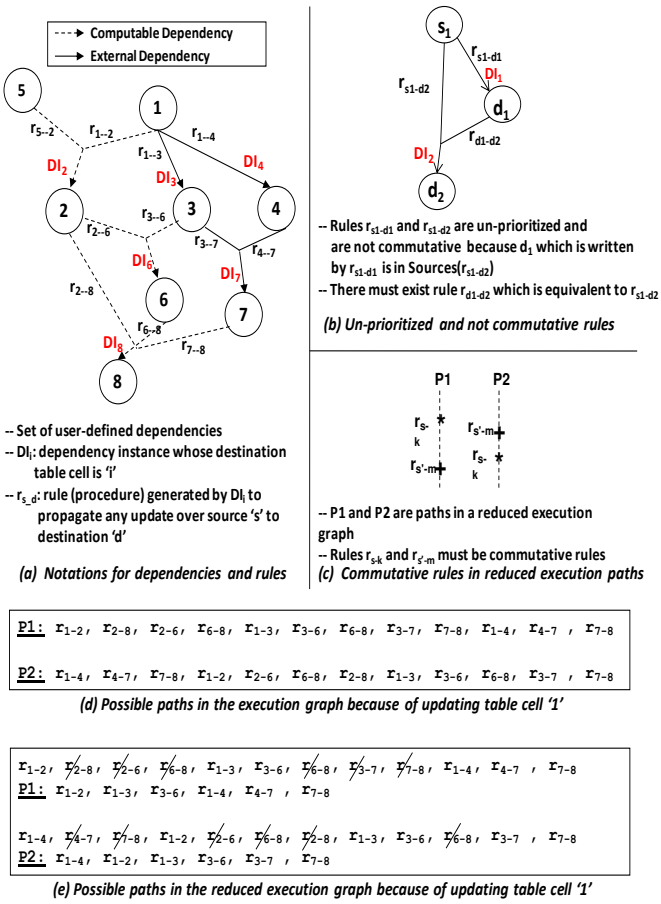


Figure 12: Example used in the Confluence analysis

In the following, we introduce the notations and definitions used in the analysis. The example in Figure 12 is used as a demonstrative example throughout the analysis.

Dependency Instance DI_k: DI_k is the dependency instance whose destination table cell is *'k'*. Since each table cell can be a destination parameter to at most one dependency instance, then a dependency instance can be uniquely identified by its destination parameter. For example, DI_8 in Figure 12(a) is the dependency instance whose destination table cell is *'8'*. The set of all dependency instances in the database is D.

Rule r_{s-d}: r_{s-d} is a rule (procedure) generated by dependency DI_d to propagate the updates over the source table cell *'s'* to the destination table cell *'d'*. For example, rules r_{2-8} in Figure 12(a) is a rule generated by dependency instance DI_8 to propagate the updates from table cell *'2'* to table cell *'8'*. The set of all rules in the database is R.

Sources(r_{s-d}): Sources(r_{s-d}) is the set of all source table cells that are read by rule r_{s-d}. These sources are the source parameters of dependency instance DI_d. Intuitively, *'s'* $\in$ $Sources(r_{s-d})$. For example, Sources(r_{2-8}) in Figure 12(a) are {*'2'*, *'6'*, *'7'*}.

Equivalent rules: Two rules $r_{s_1-d_1}$ and $r_{s_2-d_2}$ are said to be equivalent iff, starting from the same database instance, they read the same table cells, write the same table cells, and generate the same new database instance. By default, every rule is equivalent to itself.

Lemma 1 (Equivalent rules): *Two rules r_{s_1-d} and r_{s_2-d} in D are equivalent.*

Proof: Rules r_{s_1-d} and r_{s_2-d} are generated from the same dependency instance DI_d. Therefore, Sources(r_{s_1-d}) = Sources(r_{s_2-d}), the two rules write the same destination table cell *'d'*, and they execute the same functionality imposed by DI_d. Therefore, r_{s_1-d} and r_{s_2-d} are equivalent.

Execution graph EG: As defined in [**?**](Section 4), an execution graph *EG* is a directed graph in which the paths represent all possible execution sequences during the rule processing. Branching in the graph results from having different eligible commutative rules to be triggered at the same time. For example, updating table cell '1' in Figure 12(a) triggers the execution of a sequence of rules. Two possible execution paths are depicted in Figure 12(d).

Lemma 6.1 in [**?**] have mentioned six conditions that need to be false in order for rules r_i and r_j to commute. These conditions are:

1. r_i can cause r_j to be triggered.
2. r_i can un-trigger r_j by nullifying the cause for triggering r_j.
3. r_i performs an operation (insert, delete, update) that affects what r_j reads.
4. r_i insert operations may affect the update and delete operations of r_j.
5. r_i and r_j can update the same database cell.
6. any of the above 1-5 conditions with r_i and r_j reversed.

In our model, two rules $r_{s_1-d_1}$ and $r_{s_1-d_2}$ that are triggered because of an update in table cell s_1 are considered un-prioritized rules and they will both become eligible for execution at the same time. For example, rules r_{1-2}, r_{1-3}, and r_{1-4} in Figure 12 are un-prioritized rules that will all become eligible for firing when table cell *'1'* is modified. Given the two rules $r_{s_1-d_1}$ and $r_{s_1-d_2}$, we find out that all of the above conditions are guaranteed to be false except for Condition 3. In Condition 3, rule $r_{s_1-d_1}$ may perform an update operation that affects what $r_{s_1-d_2}$ reads only if $d_1 \in Sources(r_{s_1-d_2})$, i.e., the destination table cell of $r_{s_1-d_1}$ is a source parameter to $r_{s_1-d_2}$. This case is illustrated in Figure 12(b). However, if this case occurs, i.e., $d_1 \in Sources(r_{s_1-d_2})$, then there must exist another rule $r_{d_1-d_2}$ in D since d_1 is a source parameter to dependency DI_{d2}. Moreover, according to Lemma 1, rules $r_{d_1-d_2}$ and $r_{s_1-d_2}$ are equivalent. We will show next that we can generate a reduced execution graph (based on *rule overwriting* discussed below) in which $r_{s_1-d_2}$ is replaced by $r_{d_1-d_2}$. As a result, the reduced execution graph will contain the prioritized rules $r_{s_1-d_1}$ and $r_{d_1-d_2}$ which cannot be eligible for execution at the same time, and hence the commutativity property is not required.

Lemma 2 (Rule overwriting): Rule r_{s_1-d} is said to overwrite an equivalent rule r_{s_2-d} in an execution path P if r_{s_1-d} appears after r_{s_2-d} in P. As a result, r_{s_2-d} can be removed from P without affecting the final state of the database resulted from P. By default, every rule overwrites itself.

Proof: Lemma 2 is proved if the following two conditions are true:

1. The execution of r_{s_1-d} does not depend on the execution of r_{s_2-d}. That is, r_{s_1-d} does not read values written by r_{s_2-d} or by any rule that is triggered because of executing r_{s_2-d}.
2. All rules that are triggered between r_{s_2-d} and r_{s_1-d} because of firing rule r_{s_2-d} are guaranteed to be triggered again after r_{s_1-d}. That is, rules that are affected by the execution of r_{s_2-d} will be overwritten by rules that fire after r_{s_1-d}.

Condition 1 is a direct byproduct of having no cycles among the user-defined rules. With respect to Condition 2, all rules that are triggered between the execution of r_{s_2-d} and r_{s_1-d} are categorized into two categories; rules that are triggered because of the firing of r_{s_2-d} (category *A*), and rules that are triggered independently from the firing of r_{s_2-d} (category *B*). Since r_{s_1-d} modifies the same destination table cell as r_{s_2-d}, i.e., *'d'*, then all rules in category *A* must fire again after rule r_{s_1-d}. Therefore, the execution of category *A* rules that occurred between the execution of r_{s_2-d} and r_{s_1-d} will be overwritten by rules occurring after rule r_{s_1-d}. Thus, Condition 2 holds.

Reduced execution graph REG: A reduced execution graph *REG* is an execution graph in which rule r_{s_2-d} is removed from each execution path P if there exist rule r_{s_1-d} that overwrites r_{s_2-d} in *P*. An execution path in *REG* is called reduced execution path (See Figure 12(d)).

Back to the special case of having two un-prioritized rules $r_{s_1-d_1}$ and $r_{s_1-d_2}$ that do not commute with each other because they satisfy Condition 3 above. Recall that, in this case, another rule $r_{d_1-d_2}$ must exist in the dependency graph. This problem is solved in the reduced dependency graph as follows. Since rules $r_{d_1-d_2}$ and $r_{s_1-d_2}$ are equivalent, then there are two possible cases in any reduced execution path, either $r_{d_1-d_2}$ overwrites $r_{s_1-d_2}$ (Case 1), or $r_{s_1-d_2}$ overwrites $r_{d_1-d_2}$ (Case 2). In Case 1, the problem is no longer exist because $r_{s_1-d_2}$ is removed from the execution path and the existing two rules are prioritized rules. In Case 2, since $r_{s_1-d_2}$ overwrites $r_{d_1-d_2}$, then rule $r_{d_1-d_2}$ appeared before rule $r_{s_1-d_2}$ in the execution path and that is why it is overwritten. Since $r_{d_1-d_2}$ appeared before rule $r_{s_1-d_2}$, then rule $r_{s_1-d_1}$ has to be also appeared in the execution path before $r_{s_1-d_2}$ ($r_{s_1-d_1}$ has to appear before $r_{d_1-d_2}$ in any execution path). Therefore, we can safely replace rule $r_{s_1-d_2}$ by rule $r_{d_1-d_2}$ in the execution path and eliminate the problem.

The reduced execution graph has the following interesting properties:

1. Each reduced execution path contains at most one rule for each dependency DI_k, say rule r_{s-k}.
2. After the execution of rule r_{s-k}, the source parameters of of DI_k, i.e., Sources(r_{s-k}), are guaranteed not to change. The reason is that if any of the source parameters have changed after the execution of r_{s-k}, then another rule $r_{s'-k}$ would have been added to the execution path that overwrites r_{s-k}.
3. There are no equivalent rules. The reason is that if there are two equivalent rules, then the second one would have overwritten the first one.

4. Any two un-prioritized rules having the same source, e.g., $r_{s_1-d_1}$ and $r_{s_1-d_2}$, in the reduced execution path are commutative. This reason is that if $r_{s_1-d_1}$ and $r_{s_1-d_2}$ are not commutative, then we would have applied the replacement mechanism mentioned above to eliminate this case.

In a reduced execution graph, the following lemma holds.

Lemma 3 (Rule commutativity in REG): In a reduced execution graph, if two rules r_{s-k} and $r_{s'-m}$ switched their execution order in two different execution paths, then r_{s-k} and $r_{s'-m}$ are commutative.

Proof: In the case where rules r_{s-k} and $r_{s'-m}$ have the same source, i.e., $s = s'$, then r_{s-k} and $r_{s'-m}$ are commutative according to the 4^{th} property of the reduced execution graph mentioned above. In the case where $s \neq s'$, then we check the two rules against the six commutativity conditions [**?**](Lemma 6.1) and prove that all the conditions are false (Refer to Figure 12(c) for illustration). Condition 1 is guaranteed to be false because if we assumed that one of the two rules, say r_{s-k}, can trigger the other rule, say $r_{s'-m}$, then the execution path in which rule r_{s-k} is executed after $r_{s'-m}$ would form a cycle which contradicts with Theorem 1. Moreover, since neither of the two rules can modify the sources of the other rule, then Condition 2 is always false. Condition 3 is also guaranteed to be false because if one rule, say r_{s-k}, performs an operation that affects what the other rule, say $r_{s'-m}$, reads, then the path in which $r_{s'-m}$ is executed before r_{s-k} contradicts with the 2^{nd} property of the reduced execution graph mentioned above.

Based on the properties of the reduced execution graph and Lemma 3, we prove Theorem 2.

Theorem 2 (Confluence): *In a reduced execution graph generated from a set of user-defined dependencies, two different execution paths P1 and P2 are equivalent. Hence, the execution graph is confluent.*

Proof: The proof of Theorem 2 is based on re-ordering the rules in execution path *P2* to match the order of the rules in *P1*. We maintain one pointer over each execution path, initially each pointer points to the first rule. If the pointers point to equivalent rules (Refer to Lemma 1), then we move the two pointers one step. Otherwise, the pointers point to two different rules in *P1* and *P2*, say r_{s-k}, and $r_{s'-m}$, respectively. In this case, rule r_{s-k} (or one of its equivalent rules) has to appear in *P2* after $r_{s'-m}$ (other rules may exist between $r_{s'-m}$ and r_{s-k} in *P2*). If we proved that r_{s-k} in *P2* commutes with each rule before it till $r_{s'-m}$ inclusively, then we can move r_{s-k} up in *P2* to match the corresponding rule in *P1*, and then we shift the two pointers one step. Consider rule r_{i-j} that is before r_{s-k} and after $r_{s'-m}$ in *P2*. If the two rules have the same source, i.e., $i = s$, then the two rules are commutative according to the 4^{th} property of the reduced execution graph. Otherwise, rule r_{i-j} (or one of its equivalent rules) has to appear in *P1* after rule r_{s-k}. Hence, rules r_{i-j} and r_{s-k} have switched their execution order in two different paths, and according to Lemma 3, the two rules are commutative. By repeatedly applying the above steps, we can re-order the rules in *P2* to match the order of the rules in *P1* which proves that the two paths are equivalent.

Theorem 3 (Termination and Confluence): *Given a valid set of user-defined dependencies, the execution of the procedures enforcing these dependencies is guaranteed to terminate (Termination) and to generate a unique final state of the database (Confluence).*

Proof: Theorem 3 applies directly from Theorems 1 and 2.

7. PERFORMANCE ANALYSIS

We implemented *HandsOn DB* via extensions to PostgreSQL that include: (1) adding new SQL syntax for creating the real-world activity functions and modeling the dependencies, (2) adding new data manipulation operations, i.e., *invalidate()* and *validate()*, (3) augmenting mechanisms for automatically creating (or deleting) triggers when dependencies are added (or deleted), (4) introducing new query operators in PostgreSQL with the semantics presented in Section 5, and (5) adding the *Resume Function()* command for resuming pending activities. In this section, we study the overheads associated with these extensions and demonstrate the feasibility and practicality of *HandsOn DB*.

***Datasets*:** We use three datasets: *Genobase*, a real biological database of size approximately 40MB, *PubChemsubstance*, a real chemical database of size approximately 300MB, and a synthetic dataset of size approximately 450MB. *Genobase* stores the gene details of the Ecoli organism along with different mutation types. *PubChemsubstance* stores information about chemical substances, e.g., substance_ids, sources, synonyms, compounds, and atoms. The synthetic dataset is designed primarily to stress on the cascading effect of the dependencies as will be explained later. It consists of 10 tables, i.e., R_1, ..., R_{10}. Each table consists of ten attributes, i.e., c_1, c_2, ..., c_{10}, in addition to the primary and foreign keys. Each table R_{i+1} contains two foreign keys that point to the primary keys of tables R_i and R_{i-1}. Columns c_1 to c_5 are of type *integer* while columns c_6 to c_{10} are of type *text* storing strings of length varying from 100 to 1000 characters.

***Storage*:** In Figure 13, we study the storage overhead imposed from adding the *status* (one bit) and *dependency_id* (two-bytes integer) columns for each database column. The figure illustrates that the storage overhead ranges from 2% to 7% of the database size. As expected, the storage overhead is relatively insignificant. The reason is that scientific databases typically store many large-size attributes such as text and sequence fields that dominate the storage overhead. *PubChem-substance* shows the highest storage overhead because the average length of its attributes is smaller than those of the other two databases.

***Adding Dependency*:** In Figure 14, we study the average time needed for adding a new dependency. This time involves detecting whether or not a cycle exists, and creating the required triggers. In this experiment, we vary the number of generated dependencies from 2^5 to 2^{11} (the X-axis) distributed over 5 tables with an average cascading length of 2. One half of the generated dependencies has a single source table while the other half has two source tables. To create multiple non-overlapping dependencies over a single destination attribute, we divide this attribute into disjoint subsets and assume that each subset is inferred or computed using a different function. In the experiment, we study the two cases where the newly defined dependency either invalidates the destination table cells (labeled as 'With Inv-Dest') or keeps them as valid (labeled as 'Without Inv-Dest'). Figure 14 illustrates that the size of the database does not significantly affect the execution time. The reason is that the

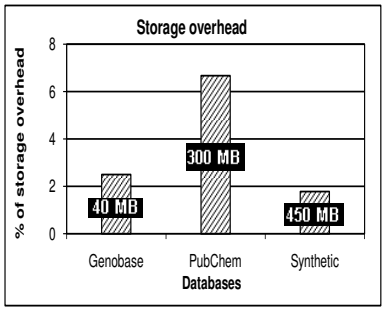


Figure 13: Storage overhead

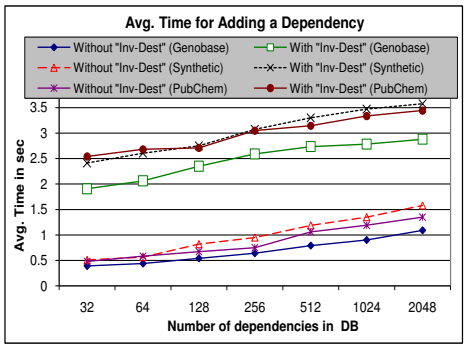


Figure 14: Adding dependency

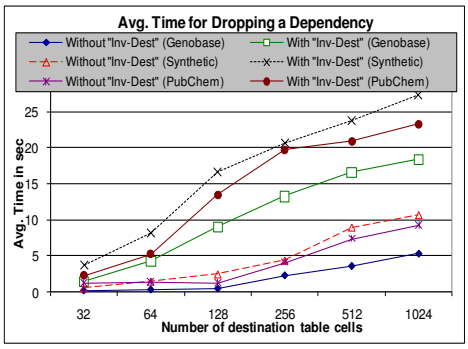


Figure 15: Dropping dependency

time taken to detect whether or not a cycle exists and to create the required triggers is not influenced much by the size of the underlying database. Also, the figure illustrates that the average time taken in the case of invalidating the destination table cells is higher than that where the destination table cells are kept valid. The reason is that invalidating the destination table cells will propagate this invalidation to all dependent data items which may span multiple tables.

***Dropping Dependency*:** In Figure 15, we measure the average time required for dropping a dependency. Initially, we add 2^{11} dependencies to each of the three databases distributed over five tables with an average cascading length of two. In this experiment, we vary the number of destination table cells that belong to the dropped dependency from 2^5 to 2^{10} (the X-axis) and measure the required time under the cases where the destination cells are either invalidated (labeled as 'With Inv-Dest') or validated (labeled as 'Without Inv-Dest'). The measured performance depends on the initial status of the database cells, e.g., invalidating table cells that are already invalid is less expensive than invalidating up-to-date cells, and the same applies for validation. Therefore, we compute each point in the figure as the average over five runs each with a different percentage of the outdated values in the destination column. Since in typical scenarios most of the database items are up-to-date, we vary the percentage of the outdated values in the destination column over the set of {0%, 5%, 10%, 15%, 20%}. Figure 15 illustrates that dropping a dependency can be an expensive operation especially when invalidating a large number of destination table cells. The overhead associated with invalidating the destination parameters of the dropped dependency is around three or four times higher than that associated with validating the destination parameters. The reason for this difference is that most of the data items in the database are already valid, and hence the validation procedure is not as expensive as the invalidation procedure. The invalidation procedure typically propagates the invalidations to more dependent table cells. More analysis on the performance of both procedures will be discussed in Figure 16. Figure 15 illustrates that the synthetic and *PubChem* databases encounter higher overhead compared to *Genobase*. The reason is that the tables of the former databases are around 8 to 10 times larger. In general, dropping a dependency is expected to be an infrequent operation especially when the number of associated destination table cells is large. Otherwise, the overhead involved in re-verifying and re-validating these destination table cells would probably dominate the overhead of the *Drop Dependency* operation.

***Manipulation Operations*:** The performance of the data manipulation operations is presented in Figure 16. In this experiment, we use only the synthetic database that is designed primarily to enable creating long cascading paths among the database tables. Each of the ten tables contains a number of tuples that varies from 1,000 to 50,000. Each table R_i contains the following dependency types among its attributes: (1) computable dependency from c_1 to c_2, (2) real-world dependency from c_2 and c_3 to c_4, and (3) computable dependency from c_4 to c_5. Each defined dependency targets a small subset of the destination column, and hence multiple dependencies can be defined over the destination column without overriding each other. The database contains also cross-table dependencies defined as follows: (1) computable dependency from $R_i.c_5$ to $R_{i+1}.c_1$, and (2) real-world dependency from $R_i.c_2$ to $R_{i+1}.c_7$. Using this database design, the length of a cascading path varies from 0 to 40 operations. In Figure 16, we study the average time needed to perform each of the *update*, *invalidate*, *validate*, or *Resume Function* operations. For the first three operations, each measurement represents the average over 50 randomly-selected table cells (five from each table). The figure illustrates that the *update* operation involves the highest cost. The reason is that the update procedure performs extra processing (including calling the user-defined functions involved in the computable dependencies[2]) regardless of whether the updated table cell is up-to-date or outdated. This is unlike the invalidate and validate procedures that may take no actions if the table cell is already invalid or valid, respectively. The cost of the *invalidate* operation is less than that of the *update* operation because if the invalidated table cell is already outdated, then the procedure terminates without any further processing. Otherwise, it involves the cost of invalidating all dependent data items. The figure illustrates also that the overhead of the *Resume Function* operation is higher than those of the *validate* and *invalidate* operations. The reason is that resuming a function updates the destination table cell, which triggers calling the appropriate user-defined functions to propagate the updates. Although resuming a function triggers an update operation, its average time is less than that of the update operation. One explanation is that the resume operation updates a table cell whose dependent items are already invalid, and hence, propagating the invalidation does not take place.

[2]The computable UDFs used in experiments involve only simple arithmetic operations, e.g., additions and subtractions.

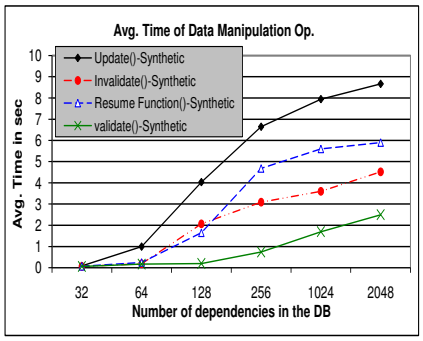


Figure 16: Manipulation operation

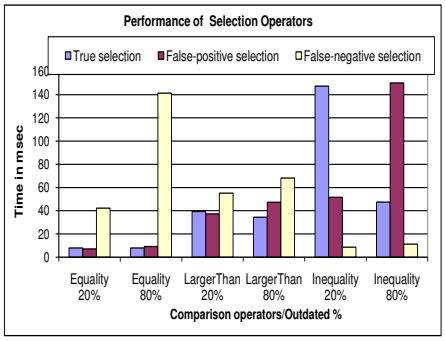


Figure 17: Selection performance

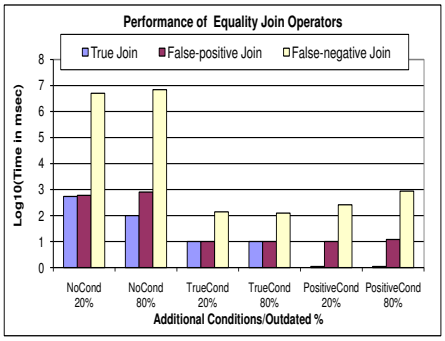


Figure 18: Join performance

***Query Operators*:** With respect to data querying, we define extended semantics for the comparison operators, e.g., =@, =+, and =-, correspond to the true, false-positive, and false-negative evaluation of the equality operators, respectively. Other operators, e.g., >, <, and <>, are extended in the same way. Queries that involve the extend operators are re-written using the standard operators according to the re-writing rules presented in Figure 19.

In Figure 17, we study the performance of the three types of selection operators over a table consisting of 50,000 tuples from the synthetic database. The select statement is in the form of `Select * From R Where R.a` *OP* `<const>`, where *OP* is one of the extended selection operators. The values in the selection column $R.a$ have a duplication factor that varies uniformly over the range from 1 to 10. Since the performance of the selection operators depends on the percentage of the outdated values in $R.a$, we run each experiment over two different percentages of the outdated values, 20% and 80%, as illustrated in Figure 17. We build B+-tree indexes over both the data column involved in the *where* clause, i.e., $R.a$, and $R.a$'s corresponding status column, i.e., $R.a\_status$. In the experiment, we consider three different types of comparison operators: equality, larger than, and inequality. In the case of equality, the *true* and *false-positive* selections have relatively lower overhead (compared to *false-negative*) because they make use of the index on the value columns to find the matching values. The *false-negative* operator utilizes the index on the status field (in the case of 20% outdated values), but performs a full-scan (in the case of 80% outdated values) which explains the difference in the execution time illustrated in Figure 17. The inequality comparison has the inverse behavior of the equality compariosn. The *false-negative* selection is rewritten as *equality* and hence its evaluation uses the index on the data column regardless of the percentage of the outdated values.

With respect to joins, we focus on studying the performance of the three types of equality joins as depicted in Figure 18. We use two relations R and S from the synthetic database, each consisting of 50,000 tuples. The Select statement is in the form of `Select * From R, S Where R.a` *OP* `S.b And <ExtraCond>`, where *OP* is one of the extended equality join operators. The values in the join attributes $R.a$ and $S.b$ are randomly generated over the range from 1 to 10,000 with a duplication factor that varies uniformly over the range from 1 to 10. Both columns and their corresponding status attributes have B+-tree indexes. In Figure 18,

	Extended operator	Re-writing rule
Unary operators	R.a =@ *<constant>*	R.a = *<constant>* and R.a_status = 0
	R.a =+ *<constant>*	R.a = *<constant>* and R.a_status = 1
	R.a =- *<constant>*	R.a <> *<constant>* and R.a_status = 1
Binary operators	R.a =@ S.b	R.a = S.b and (R.a_status = 0 and S.b_status = 0)
	R.a =+ S.b	R.a = S.b and (R.a_status = 1 or S.b_status = 1)
	R.a =- S.b	R.a <> S.b and (R.a_status = 1 or S.b_status = 1)

⋆Other comparison operators, e.g., '>', '<', '<>', have similar rules

Figure 19: Re-writing rules of the extended operators

we consider three different scenarios that trigger different query plans: (1) the scenario where there are no extra conditions in the select statement, called *NoCond*, (2) the scenario where there is a *true* equality selection condition on $R.a$, called *TrueCond*, and (3) the scenario where there is a *false-positive* equality selection condition on $R.a$, called *PositiveCond*. Each scenario is evaluated under 20% and 80% percentages of outdated values in the joined columns, i.e., $R.a$ and $S.b$. The Y-axis in the figure is a logarithmic scale.

In the case where the query includes only the join condition (*NoCond* case), the *true* and *false-positive* join operators use a hash-based join algorithm since the join condition is an equality between $R.a$ and $S.b$. The *true* join has less execution time in the case where the outdated percentage is 80% because the query optimizer uses the index on the *status* column to retrieve only the 20% up-to-date values that can contribute to the join. In contrast, the *false-negative* join operator uses a nested-loops join and that is why it involves high overhead. In the case where the query includes a *true* equality selection on $R.a$(*TrueCond*), the values from $R.a$ that satisfy the selection predicate are all up-to-date. Hence, for the *false-positive* and *false-negative* joins, the values from $S.b$ column have to be outdated. In this case, the re-written predicates for the *false-positive* and *false-negative* joins will only contain conjunctive predicates. In the case where the query includes a *false-positive* equality selection on $R.a$(*PositiveCond*), the values from $R.a$ that satisfy the selection predicate are all outdated. Hence, the result set from the *true* join is always empty because the *true* join requires the joined values to be both up-to-date. This explains the very low overhead involved in this join type.

8. CONCLUSION

In this paper, we proposed *HandsOn DB* system for supporting dependencies that involve real-world activities while maintaining the consistency of derived data under update and query operations. *HandsOn DB* addresses several challenges that include: (1) keeping track of the potentially invalid data items and reflecting their status in the query results, (2) introducing new semantics for query operators that enable evaluating queries on either valid data only (no false-positives), or both valid and potentially-invalid data (include false-positives), (3) proposing new mechanisms for invalidating, revalidating, and curating the data items, and (4) proposing dynamic techniques through database triggers for enforcing the dependencies without materializing them. We studied the correctness of execution and proved that database operations are guaranteed both to terminate and to generate a unique final state of the database. We also evaluated experimentally the performance of *HandsOn DB* and demonstrated the feasibility and practicality of its operations.